REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*: 04-2002

2. REPORT DATE: FINAL

3. DATES COVERED *(From - To)*: May 1999 - Sep 2002

4. TITLE AND SUBTITLE
Wavelet Digital Signal Processing of Undersea Acoustic Data

5a. CONTRACT NUMBER

5b. GRANT NUMBER
N00014-98-1-0828

5c. PROGRAM ELEMENT NUMBER

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

6. AUTHOR(S)
Ioup, Juliette W.
Ioup, George E.
Wheatley, Joseph S.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
University of New Orleans
New Orleans, LA 70148

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Office of Naval Research
Ballston Centre Tower One
800 North Quincy St.
Arlington, VA 22217-5660

10. SPONSOR/MONITOR'S ACRONYM(S)
ONR

11. SPONSORING/MONITORING AGENCY REPORT NUMBER

12. DISTRIBUTION AVAILABILITY STATEMENT
Approved for Public Release; Distribution is Unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT Chirplet signal reconstruction algorithms have been developed using MATLAB. A Flexible Chirplet Transform algorithm has been developed. Building and implementation of chirplet reconstruction algorithms have been completed successfully. Feature extraction and noise removal for low frequency acoustic chirp signals have been completed using scalar wavelet, wavelet packet, multiwavelet, and chirplet and Fourier techniques. Comparison of these methods has been performed, and the results have been analyzed. Adaptive wavelet transform algorithms via lifting have been developed and are currently being used to design specific wavelet transform for low frequency broadband simulated chirp signals.

15. SUBJECT TERMS
digital signal processing
wavelet transforms
simulated undersea acoustic data

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U			UU	10	Juliette W. Ioup
					19b. TELEPONE NUMBER *(Include area code)*: 504 280-6715

Wavelet Digital Signal Processing of Undersea Acoustic Data
ONR Grant Number N00014-99-1-0828

FINAL REPORT
April 2002

Juliette W. Ioup, George E. Ioup, and Joseph S. Wheatley
Department of Physics
University of New Orleans
New Orleans, LA 70148
Phone: 504 280 6715 FAX: 504 280 6048
Email: jioup@uno.edu, geioup@uno.edu, wheatley@datastar.net

WORK COMPLETED

Chirplet signal reconstruction algorithms have been developed using MATLAB. A Flexible Chirplet Transform algorithm has been developed. Building and implementation of chirplet reconstruction algorithms have been completed successfully. Feature extraction and noise removal for low frequency acoustic chirp signals have been completed using scalar wavelet, wavelet packet, multiwavelet, and chirplet and Fourier techniques. Comparison of these methods has been performed, and the results have been analyzed. Adaptive wavelet transform algorithms via lifting have been developed and are currently being used to design specific wavelet transforms for low frequency broadband simulated chirp signals.

TECHNICAL RESULTS

The chirplets investigated in this research are Gaussian amplitude-modulated signals parameterized by their location in time, location in frequency, chirp rate, and time duration. Signal reconstruction based on chirplet reconstruction theory is dependent upon at least five parameters per

chirplet: amplitude, time, frequency, chirp rate, and signal duration (Mihovilovic and Bracewell, 1991, 1992).

Table 1 shows the dependencies of six types of data representations of transforms on various parameters. A time series or Shannon representation provides data values as a function of time. The Fourier transform describes the data in terms of frequency values. The Gabor or time-frequency two-dimensional plot shows both time and frequency. The wavelet transform also includes a scaling factor. The continuous chirplet transform adds a chirp rate parameter; and using multiple chirplets includes a dispersion rate and a time-frequency tile size.

Table 1.	Time	Freq	Scale	Chirp rate	Dispersion rate	TF tile size
Shannon	X					
Fourier		X				
Gabor	X	X				
Wavelet	X	X	X			
Continuous Chirplet	X	X	X	X		
Multiple Chirplet	X	X	X	X	X	X

MATLAB code is generated as an adaptation of O'Neill's (2000) chirplet transform codes and an adaptive wavelet transform code (Chapa and Rao, 2000).

Figures 1 and 2 are generated using a maximum likelihood estimation routine for estimating the chirplet parameters that was written by O'Neill (O'Neill et al., 2000). The signals in the figures are whale whistles represented as a sum of chirplets. Figure 1 shows the spectrogram of a whale whistle, number 61 from the NUWC data set (O'Neill et al., 2000). The dynamic range in the spectrogram is 50 dB. Below the spectrogram is a time-series of one time trace, and to the left is the log spectrum of the trace. Figure 2 shows the same whale whistle with the noise removed via wavelet methods. Below the spectrogram is the envelope of the time series. The denoised approximation was made with 8 chirplets and agrees well with the original. A signal represented by 8 chirplets, each containing 5

parameters, means 40 parameters must be used to identify it, creating a computationally intensive approach to signal classification.

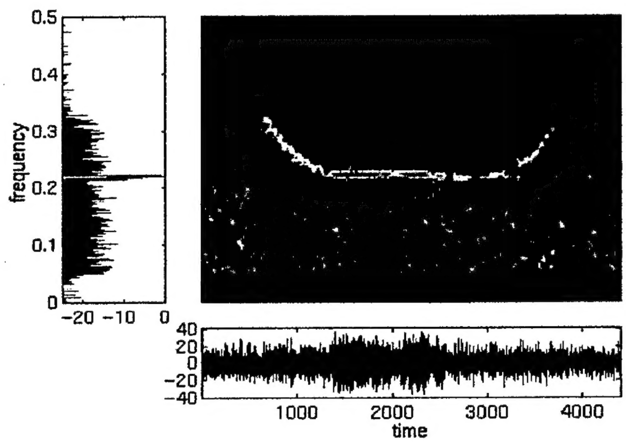

Figure 1. Spectrogram of whale whistle 61 from NUWC data set with sample time trace and frequency spectrum.

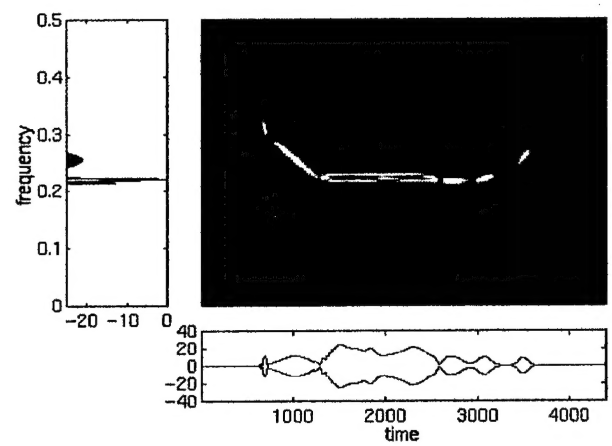

Figure 2. Denoised whale whistle of Fig. 1 reconstructed with 8 chirplets.

Figure 3 shows a synthetic chirp at the top. It has approximately constant amplitude and frequency increasing with time (upsweep chirp). There is very little noise present and the signal-to-noise ratio (SNR) is 8. The second curve shows the chirp with Gaussian white noise added such that the SNR is 1.5. Two noise removal techniques were applied to the noisy chirp. The Fourier lowpass filtered chirp is shown in the next curve and the wavelet denoised chirp at the bottom. The lowpass filter cutoff frequency is 500 Hz. The wavelet used is a Daubechies 5 (db5) with 5 levels. The thresholds for denoising are manually set at the values given in Table 2.

Table 2.	level	threshold
	5	4.076
	4	8.946
	3	10.03
	2	9.423
	1	7.893

Figure 4 contains the spectrograms calculated from their counterparts in Figure 3. The top figure shows the noise-free chirp, and the upsweep in frequency is clear. The chirp is still visible in the noisy second figure, but noise removal is needed to clarify the signal. The lowpass filter shown in the next figure removes frequencies above 400 Hz, including those present in the chirp, without reducing the lower frequencies very much. In the bottom figure showing the wavelet denoising the chirp character is again visible. It is evident that the wavelet algorithm outperforms the Fourier method in this case.

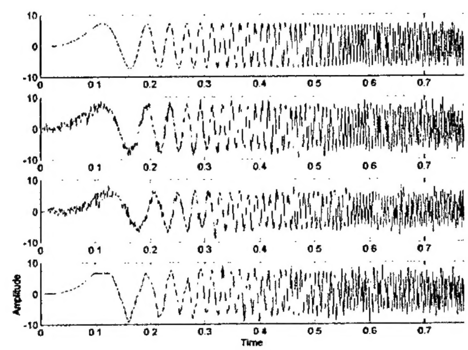

Figure 3. Top: Synthetic noise free upsweep chirp. Second: Noisy chirp with SNR 1.5. Third: Lowpass filtered noisy chirp; cutoff frequency 500 Hz. Bottom: Wavelet denoised noisy chirp; db5 wavelet, level 5; thresholds set manually.

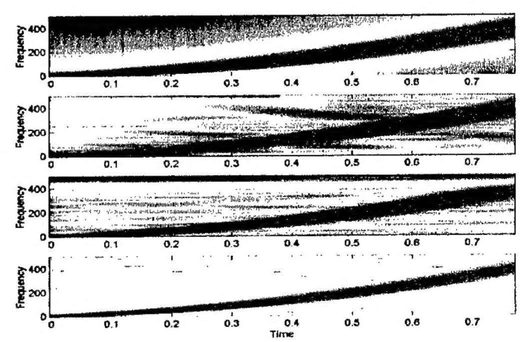

Figure4.Spectrograms corresponding to the signals shown in Fig. 3.

Wavelet denoising allows more signal energy to be retained while still removing unwanted noise. Fourier analysis removes signal structure as well as unwanted noise, as can be seen in Figure 5, which is the lowpass filtered result using a lowpass cutoff of 200 Hz.

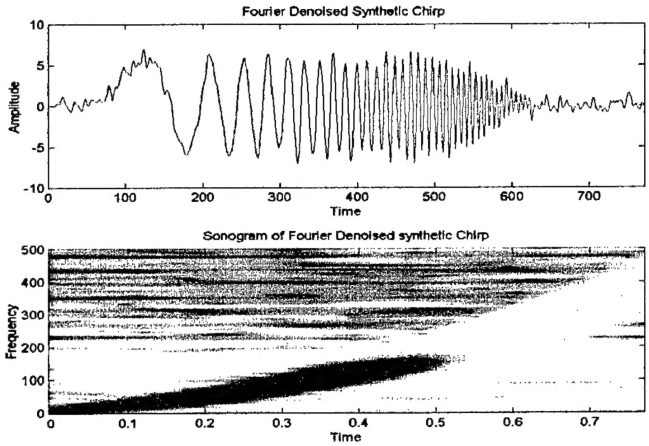

Figure 5. Top: Lowpass filtered noisy chirp; cutoff frequency 200 Hz. Bottom: Spectrogram.

Wavelet packet denoising as well as wavelet denoising is also tested. Figure 6 shows a comparison of the Fourier lowpass filter (top; same as 3rd part of Fig. 4), single wavelet denoising (center; same as bottom of Fig. 4), and wavelet packet denoising (bottom). The wavelet used with the wavelet packet denoising was a Daubechies 5, level 5. The tree was cut at level 5. The threshold is 6.

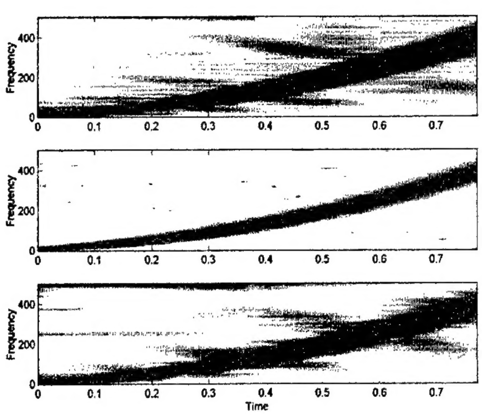

Figure 6. Top: Noisy synthetic chirp; same as second spectrogram in Fig. 4. Middle: Wavelet denoised noisy chirp; same as bottom of Fig. 4. Bottom: Wavelet packet denoised noisy chirp; db5 wavelet, level 5; threshold 6.

Table 3 shows the energy retained and the amplitude SNRs for the noisy chirp using the noise removal techniques discussed above. The lowpass filtered result retains more of the energy than either wavelet technique, but some of this energy is noise rather than signal. The SNR for single wavelet denoising is larger than for wavelet packet denoising, and both wavelet techniques have larger SNR values than the lowpass filter.

Table 3.

	Energy retained	**Amplitude SNR**
Low-noisy data	100%	8.0
Noisy data	100%	1.5
Lowpass filtered	84%	1.8
Wavelet denoised	71%	2.6
Wavelet Packet denoised	76%	2.1

Figure 7 shows another wavelet denoising of a noisy synthetic chirp using the Haar wavelet, level 5, with a threshold of 6 instead of the Daubechies dB5 wavelet, assuming unscaled white additive noise. The difference in character of the denoised result is attributed to the box structure of the Haar wavelet.

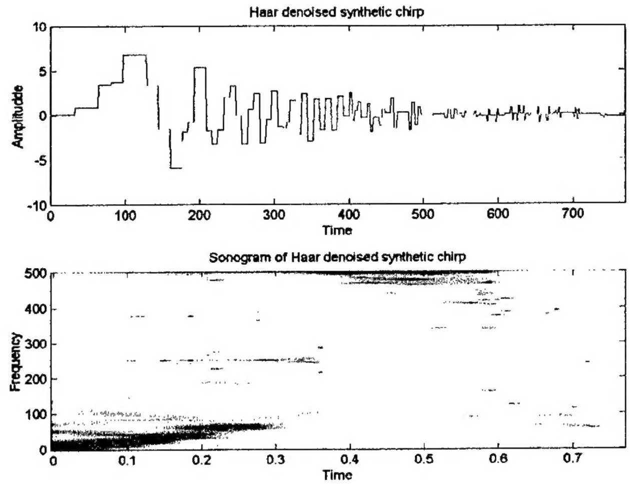

Figure 7. Wavelet denoised noisy synthetic chirp using Haar wavelet denoising, level 5, using an automatic soft threshold of 10. Top: Denoised time signal. Bottom: Spectrogram.

PRESENTATIONS

A report on this research, “Wavelet Denoising of Undersea Acoustic Data,” was presented at the ONR Technical Passive Peer Review at NUWC in Newport, RI, in October 2000.

At the Chicago meeting of the Acoustical Society of America in June 2001 a paper was presented giving some results of this research (Wheatley et al., 2001a). The abstract was published in the Journal of the Acoustical Society of America and is included in the Appendix to this report.

"Denoising of Low Frequency Chirps Using Multiple Mother Wavelets" was presented as a dissertation prospectus for the Ph.D. in Engineering and Applied Science Program of the University of New Orleans, at Stennis Space Center, MS, in July 2001.

"Multi-Wavelet Detection and Denoising of Low Frequency Chirp Signals Using Adaptive Wavelet Methods" was presented at an ONR Sponsored signal processing program review at the University of New Orleans in August 2001.

A paper presenting further results was given at the meeting of the Acoustical Society of America in Ft. Lauderdale in December 2001 (Wheatley et al., 2001b), and the abstract was also published in the Journal of the Acoustical Society of America and is included in the Appendix to this report.

APPENDIX

Joseph S. Wheatley, Juliette W. Ioup, and George E. Ioup, 2001a, Wavelet detection and denoising of low frequency chirp signals, presented at the Acoustical Society of America, Chicago, 4-8 Jun 2001, and abstracted in Jour. Acoust. Soc. Am. 109, 2296.

The detection and classification of underwater acoustic signals embedded in noise is a fundamental problem of interest to the Navy. The use of wavelet transforms is a recent development in digital signal processing that has been applied in many different areas. A particular type of wavelet is the chirplet, which includes frequency variation as well as time shift and scaling. The analysis of low-frequency signals containing multiple chirps using wavelet and chirplet techniques is demonstrated. Examples of low-frequency synthetic chirp signals are generated. Denoising and feature extraction of these signals using various wavelets with wavelet packet techniques are described.

Joseph S. Wheatley, Juliette W. Ioup, and George E. Ioup, 2001b, Multi-wavelet detection and denoising of low-frequency chirp signals using adaptive wavelet methods, presented at the Acoustical Society of America, Ft. Lauderdale, 3-7 Dec 2001, and abstracted in Jour. Acoust. Soc. Am. 110, 2765.

The detection and classification of underwater acoustic signals embedded in noise is a fundamental problem of interest to the signal processing community. The use of wavelet transforms is a recent development in digital signal processing which has been applied in many different areas. A particular type of wavelet is the chirplet, which includes frequency variation as well as time shift and scaling. Both linear and polynomial chirp signals are present in underwater acoustic signals generated by such sources as biologics, ships, and submarines. Distinguishing the features of these chirps relative to other ambient noise shows promise as an initial step in classification of underwater acoustic signals. Removal of unwanted broadband signal components via wavelet methods has been shown to outperform other noise removal processes such as low-pass and high-pass filtering and Weiner filtering. Examples of low-frequency simulated chirp signals with additive noise have been generated. A multi-wavelet packet method for detection and denoising low-frequency signals containing multiple chirps embedded in noise using a specific wavelet designed for polynomial chirp signals is shown. [Research supported in part by ONR.]

REFERENCES

R. G. Baraniuk and D. L. Jones, 1993a, A Signal-Dependent Time-Frequency Representation: Optimal Kernel Design, IEEE Trans. Sig. Proc., **41**, 1589-1602.

R. G. Baraniuk and D. L. Jones, 1993b, Shear Madness: New Orthonormal Bases and Frames Using Chirp Functions, IEEE Trans. Sig. Proc., **41**, 3543-3549.

R. G. Baraniuk and D. L. Jones, 1996, Wigner-Based Formulation of the Chirplet Transform, IEEE Trans. Sig. Proc., **44**, 3129-3135.

A. Bruce, D. Donoho, and H-Y. Gao, 1996, Wavelet analysis: IEEE Spectrum, October 1996, 26-35.

A. Bultan, 1999, A Four-Parameter Atomic Decomposition of Chirplets, IEEE Trans. Sig. Proc., **47**, 731-745.

J. O. Chapa and R. M. Rao, 2000, "Algorithms for Designing Wavelets to Match a Specified Signal," IEEE Trans on Signal Processing 48, No. 12, pp. 3395.

R. Claypoole and R. G. Baraniuk, 1998, Adaptive Wavelet Transforms via Lifting, Proc. IEEE Int. Conf. Acoust., Speech, Sig. Proc.-ICASSP '98.

Ingrid Daubechies, 1992, Ten lectures on wavelets, SIAM, Philadelphia, PA.

Marcella E. Dean, George E. Ioup, Juliette W. Ioup, and Lisa A. Pflug, 2000, Wavelet Transforms as Functional Inputs to Passive Correlation Detectors in Underwater Acoustics, presented at the Minisymposium on Computing in Underwater Acoustics at the SCC 2000 Conference, 26-28 Oct 2000, University of Southern Mississippi, Hattiesburg, MS.

C. He and J. M. F. Moura, 1998, Focused detection via multiresolution analysis, IEEE Trans. on Signal Proc., Special Issue on Theory and Applications of Filter Banks and Wavelet Transforms 46, 1094-1104.

Q. Q. Huynh, L. N. Cooper, N. Intrator, and H. Shouval, 1998, Classification of underwater mammals using feature extraction based on time-frequency analysis and BCM theory, IEEE Trans. on Signal Proc. 46, 1202-1207.

Juliette W. Ioup and George E. Ioup, 1998, Noise removal and compression using a wavelet transform, presented at the 1998 Society of Exploration Geophysicists International Exposition and Annual Meeting and published in the Extended Abstracts, 1076-1079.

Juliette W. Ioup and George E. Ioup, 1999, Fourier and Wavelet Transform Analyses of Data from Hurricane Camille, presented at The Impact of Hurricane Camille: A Storm Impact Symposium to Mark the 30th Anniversary, New Orleans, LA, 17-18 Aug 99, and published in the Program Abstracts.

X-G. Li, M. D. Sacchi, and T. J. Ulrych, 1996, Wavelet transform inversion with prior scale information: Geophysics, **61**, 1379-1385.

A. Maguer and R. Belle, 1993, Wavelet Detection of Real Propagating Signals, in Acoustic Signal Processing for Ocean Exploration, J. Moura and I. Lourtie, editors, Kluwer, 535-540.

S. G. Mallat, 1989, A theory for multiresolution signal decomposition: The wavelet representation: IEEE Trans. pattern anal. machine intell. **11**, 674-693.

S. Mann and S. Haykin, 1995, The Chirplet Transform: Physical Considerations, IEEE Trans. Sig. Proc., **43**, 2745-2761.

D. Mihovilovic and R. N. Bracewell, 1991, Adaptive chirplet representation of signals on time-frequency plane, Electron. Lett., **27**, 1159-1161.

D. Mihovilovic and R. N. Bracewell, 1992, Whistler Analysis in the Time-Frequency Plane Using Chirplets, J. Geophys. Res. **97**, 17,199-17,204.

Antonio M. Morgan, Juliette W. Ioup, George E. Ioup, and George B. Smith, 2001, Wavelet analysis of acoustic Green's functions in a shallow ocean environment, presented at the Acoustical Society of America, Chicago, 4-8 Jun 2001, and abstracted in Jour. Acoust. Soc. Am. 109, 2297.

Jeffrey C. O'Neill, 2000, "Discrete TFD's – Time Frequency Analysis Software", private communication.

J. C. O'Neill, P. Flandrin and W. C. Karl, 2000, "Sparse Representations with Chirplets via Maximum Likelihood Estimation," submitted to Eurasip Signal Processing.

W. A. Press, S. A. Tukolsky, W. T. Vetterling, and B. P. Flannery, 1992, Numerical Recipes, Second edition, Cambridge Univ. Press, Cambridge.

S. Qian and D. Chen, 1999, Joint Time-Frequency Analysis, IEEE Signal Processing Magazine, March 1999, 53-67.

N. Saito and R. R. Coifman, 1997, Extraction of geological information from acoustic well-logging waveforms using time-frequency wavelets, Geophysics, **62**, 1921-1930.

L. Sibul, R. Young, and M. Fowler, 1993, Optimum signal processing and medium characterization in the time-frequency and wavelet transform domains, in Acoustic Signal Processing for Ocean Exploration, J. Moura and I. Lourtie, editors, Kluwer, 523-534.

F. B. Shin and D. H. Kil, 1996, Full-spectrum signal processing using a classify-before-detect paradigm, J. Acoust. Soc. Am. 99, 2188-2197.

G. Strang and T. Nguyen, 1996, Wavelets and Filter Banks, Wellesley-Cambridge Press, Wellesley, MA.

M. K. Tsatsanis and G. B. Giannakis, 1993, Time-Varying System Identification and Model Validation Using Wavelets, IEEE Trans. Sig. Proc., **41**, 3512-3523.

R. J. Vaccaro and T. Chen, 1998, The Past, Present, and Future of Underwater Acoustic Signal Processing, IEEE Signal Processing Magazine, July 1998, 21-51.

J.-J. Wang and J. Zhou, 1999, Aseismic Designs Based on Artificial Simulations, IEEE Signal Processing Magazine, March 1999, 94-99.

L. G. Weiss, 1994, Wavelets and Wideband Correlation Processing, IEEE Signal Processing Magazine, January 1994.

L. G. Weiss, and T. L. Dixon, 1997, Wavelet-based denoising of underwater acoustic signals: J. Acoust. Soc. Am, **101**, 377-383.

Joseph S. Wheatley, Juliette W. Ioup, and George E. Ioup, 2001a, Wavelet detection and denoising of low frequency chirp signals, presented at the Acoustical Society of America, Chicago, 4-8 Jun 2001, and abstracted in Jour. Acoust. Soc. Am. 109, 2296.

Joseph S. Wheatley, Juliette W. Ioup, and George E. Ioup, 2001b, Multi-wavelet detection and denoising of low-frequency chirp signals using adaptive wavelet methods, presented at the Acoustical Society of America, Ft. Lauderdale, 3-7 Dec 2001, and abstracted in Jour. Acoust. Soc. Am. 110, 2765.